

COMPARATIVE EVALUATION OF ANN AND LMS BASED ALGORITHMS FOR ADAPTIVE NOISE CANCELLATION

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Abstract

The major hindrance to effective speech communication is the presence of surrounding noise and interference that tend to mask and corrupt the intelligent part of the signal. To remove the noisy components of the speech signals, adaptive noise cancellation (ANC) technique has been found efficient. In literature, several algorithms have been developed for filter coefficients adjustment for ANC systems, one of which is the least mean square (LMS). In this study, artificial neural network (ANN) based ANC technique has been proposed and compared with the conventional LMS. The algorithms were implemented and tested with a real time noisy speech signal. Simulation results are also presented to support the experimental and mathematics analysis. The performance analysis has been evaluated in terms of the means square error (MSE) of the algorithms. The developed ANN based algorithm gives a better MSE value compared to LMS when applied on speech signal.

Keywords: Adaptive filtering, Adaptive Noise Cancellation, Least Mean Square, Mean Square Error, Artificial neural network, Variable step size

1. Introduction

Noise removal from speech signal is a classical problem in the field of signal processing. In recent years, adaptive filtering has become one of the effective and popular approaches used for the processing and analysis of signal of any kind, including speech, respiratory and other biomedical signals (Sankar *et al.*, 2010). Adaptive filters are capable of detecting and tracking of the dynamic variations of the non-stationary signals. It is well known that adaptive filters are self-adjusting so that they change their impulse response according to the input signal. Therefore, they can distinguish pattern variation in the ensemble and thus obtain a better signal estimation (Nagle and Sharma, 2011).

For many speech related applications such as hands-free telephony, hearing aids and teleconferencing, recovering clean speech in environment with background acoustic noise has been a research focus for many years (Mohsen *et al.*, 2016; Abdulrazaq *et al.*, 2013). Several techniques have been developed to enhance and regenerate the clean speech signal by removing the predictable or unpredictable noise component (Lakshmikanth *et al.*, 2014; Paulo, 2008). One way to remove noise is by using basic noise reduction method where the corrupted signal is passed through a noise reduction system to get a clean speech signal which will be similar to the original signal (Bactor and Garg, 2012). Another method is the spectral-subtraction-based noise reduction (SSBNR) approach in which the system operates in the frequency domain and assumes that the spectrum of the input noisy signal can be expressed as the sum of the speech spectrum and the noise spectrum (Zhixin, 2011). The noise spectrum is first estimated and then subtracted from the noisy speech spectrum to get the clean speech spectrum (Bactor and Garg, 2012).

In the adaptive noise cancellation (ANC) filtering technique, the unwanted noise is removed from a received signal by passing the corrupted signal through a filter that tends to suppress the noise while leaving the desired signal unchanged, this operation is controlled in an adaptive manner in order to obtain an improved signal-to-noise ratio (SNR) (Abdulrazaq *et al.*, 2013). The ANC techniques uses adaptive algorithm that enables the filter to adaptively learn the statistical characteristics of signals by changing the filter coefficient in accordance to a certain present rules in order to achieve desired goals (Radek *et al.*, 2015; Abdulrazaq *et al.*, 2013). The basic adaptive algorithms which are widely used for performing weight update of adaptive filters are: the least mean square

(LMS), Normalized Least mean square (NLMS) and the recursive least square (RLS) algorithm (Paulo, 2008). LMS has probably become the most popular for its robustness, good tracking capabilities and simplicity in stationary environment. RLS is best for non-stationary environment with high convergence speed at the cost of higher complexity. Therefore, NLMS provide a tradeoff between convergence speed and computational complexity of these algorithms (Paulo, 2008). However, artificial neural network (ANN) also possess a unique adaptation characteristic through weight adjustment for learning and prediction to solve non-stationary statistical problem. Therefore, in this paper, artificial neural network based algorithm has been developed and the performance have been compared with the conventional LMS based algorithm in tracking and generalizing the noise signal pattern so as to perform adaptive noise filtering in a noisy signals.

2. Materials and Methods

2.1 Overview of Adaptive Noise Cancellation Concept

A typical ANC system is shown in Figure 1. Two input signals, $d(k)$ and $x(k)$, are applied simultaneously to the adaptive filter. The signal $d(k)$ is the corrupted signal containing both the desired signal, $s(k)$ and the noise $n(k)$, assumed to be uncorrelated to each other. The signal, $x(k)$ is a measure of the contaminating signal which is correlated in with $n(k)$, $x(k)$ is processed by the digital filter to produce an estimate $y(k)$ of $n(k)$. An estimate of the desired signal, $e(k)$ is then obtained by subtracting the digital filter output $y(k)$, from the contaminated signal (Abdulrazaq et al., 2013). The ANC system is presented in figure 1.

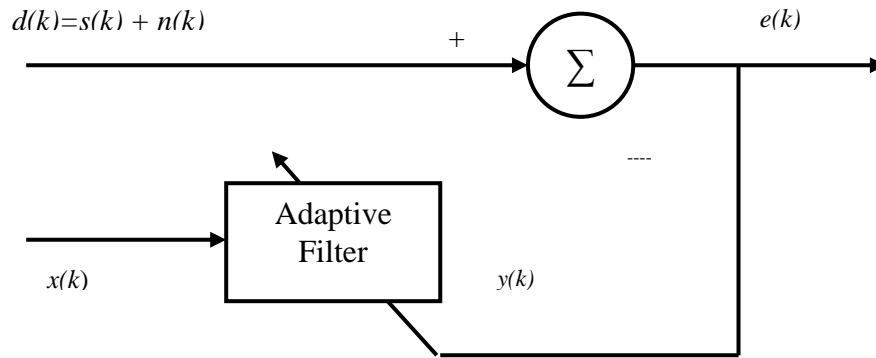


Figure 1: Adaptive Noise Canceller

2.2 Least Mean Square (LMS) Algorithm

LMS Algorithm is a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and actual signal). It is a stochastic gradient descent method in which the filter is only adapted based on the error at the current time (Nagle and Sharma, 2011).

LMS which is a linear filtering algorithm consist of two basic processes which are the filtering and adapting process. The filtering process involves computing the output $y(k)$ of the adaptive filter in response to the vector input signal $x(k)$ and generating the estimated error $e(k)$ by comparing this output $y(k)$ with the desired response $d(k)$.

Therefore; filter output $y(k)$ is;

$$y(k) = \sum_{n=0}^{N-1} w(k) x(n-k) = w^T x(n) \quad (1)$$

where: n is number of iteration

The error signal is calculated by;

$$e(k) = d(k) - y(k) \quad (2)$$

The adaptive process on the other hand involves the automatic adjustment of the parameters $w(k+1)$ of the filter in accordance with the estimation error $e(k)$ signal (Jan, 2011).

$$w(k+1) = w(k) + \mu e(k)x(k) \quad (3)$$

where: $w(k)$ is the current weight value vector, $w(k+1)$ is the next weight value vector, $x(k)$ is the input signal vector, $e(k)$ is the filter error vector, and μ is the convergence factor which determine the filter convergence speed and overall behavior (Zhixin, 2011). Figure 2 depicts the adaptation process of the LMS algorithm.

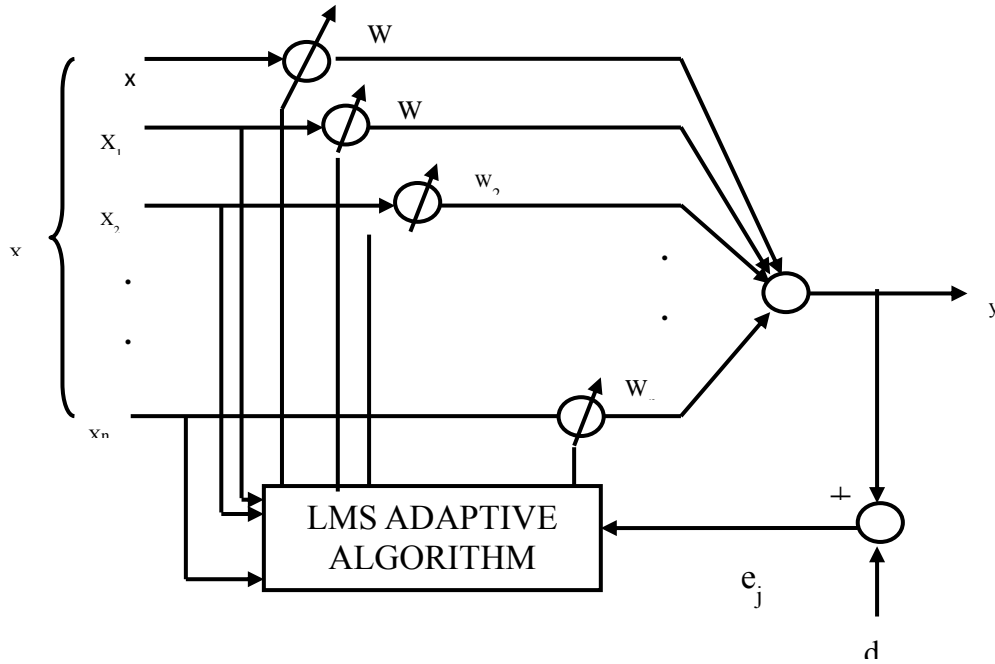


Figure 2: Adaptation process of the LMS algorithm

2.3 Artificial Neural Network (ANN)

Artificial neural networks computational model is broadly inspired by the organization of the biological nervous system. Its most important feature is the ability to learn and identify correlated patterns between inputs data sets and corresponding target values. After learning, it can be used to predict the outcome of new independent input data. Unlike conventional problem-solving algorithms, neural networks have the ability to self-organize in order to enable segmentation or coarse coding of data (Charu *et al.*, 2006). Therefore, the flexibility and self adjusting to sensed input give ANN consideration as a good tool in adapting signal processing (Girish, 2009).

The simplified mathematical representation of the neural network is given in Figure 3.

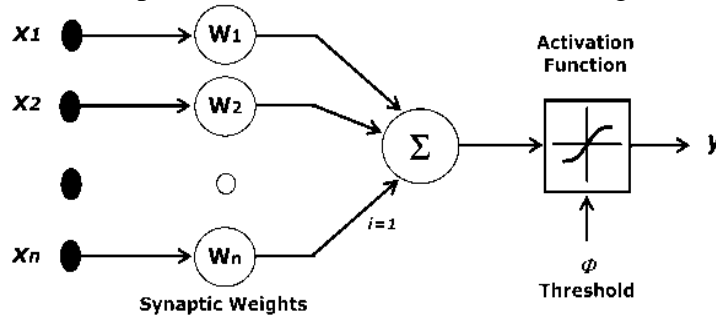


Figure 3: Mathematical representation of neural network

In recent researches, ANN has been found to be an important technique for classification, optimization and prediction problem (Sheeja, 2009). Among its practical application includes the development of neural network for forecasting financial and economic time series (Bactor and Garg, 2012), artificial neural network modelling for adsorption of dyes from aqueous solution using rice husk carbon (Khonde and Pandharipande, 2012), neural network based model reference to adaptively control the ship steering system (Jin and Dongbin, 2005), adaptive digital filter design for linear noise cancellation using neural networks (Nikhil, and Rajesh, 2015), evaluation of the performance of artificial neural networks in estimating reference evapotranspiration with minimal meteorological data (Diamantopoulou *et al.*, 2011) and neural network approach for adaptive noise cancellation (Ramanpreet and Simarpreet, 2011).

2.4 Development of ANN based Adaptive Filtering Algorithm

The block diagram of the developed ANN based algorithm is shown in Figure 4. In this case, the neural network is trained to estimate the noisy component $n(k)$ of the primary input signal.

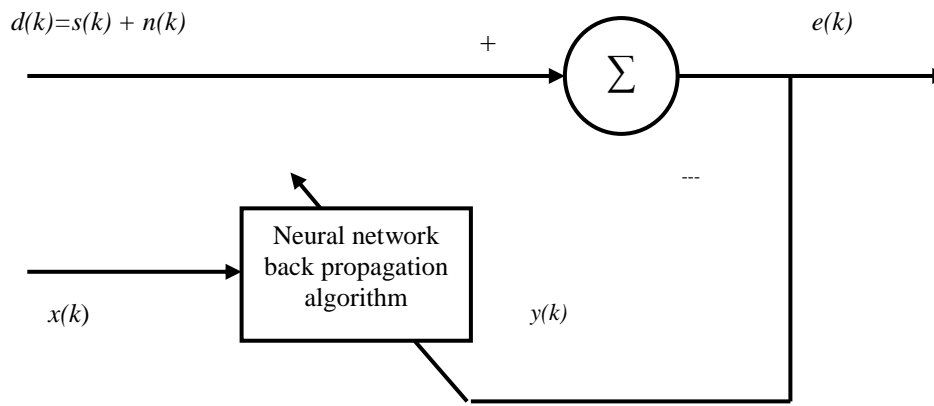


Figure 4: The Block Diagram of the Proposed Neural Network System

The primary signal input is the corrupted signal which is the combination of the desired signal $d(k)$ and the noise signal $x(k)$. It is obtained using;

$$s(k) = d(k) + x(k) \quad (4)$$

Where $s(k)$ is the speech signal, $d(n)$ is the input signal i.e the combination of speech signal and noise signal and $x(k)$ is the noise signal only.

In developing the ANN based model, sine wave is also generated as the desired signal using the general sinusoidal equation given by;

$$d(n) = A \sin(\omega t + \phi) \quad (5)$$

where A is the amplitude and ϕ is the phase angle

Also, the reference signal $x(k)$ is also correlated with the noisy signal component of the primary input. The autocorrelation of the noise signal is also computed by:-

$$R_{xx}(l) = \sum x(k)x(k-l) \quad (6)$$

Where R_{xx} is the autocorrelation of noise signal.

$x(k)$ is the present vector value of the noise signal

$x(k-l)$ is the next vector value of the noise signal.

The algorithm for the developed ANN based system is summarized by the following steps.

- Step 1: ANN weights are initialized randomly
- Step 2: ANN hidden layer output is computed.
- Step 3: The network output is computed.
- Step 4: The output error is also computed.

Step 5: Error is minimized by back-propagation.

Step 6: Weight coefficients were updated.

The ANN architecture used in this work is a two-layer feed-forward network, with sigmoid hidden as limiting function. The architecture is as shown in Figure 5:

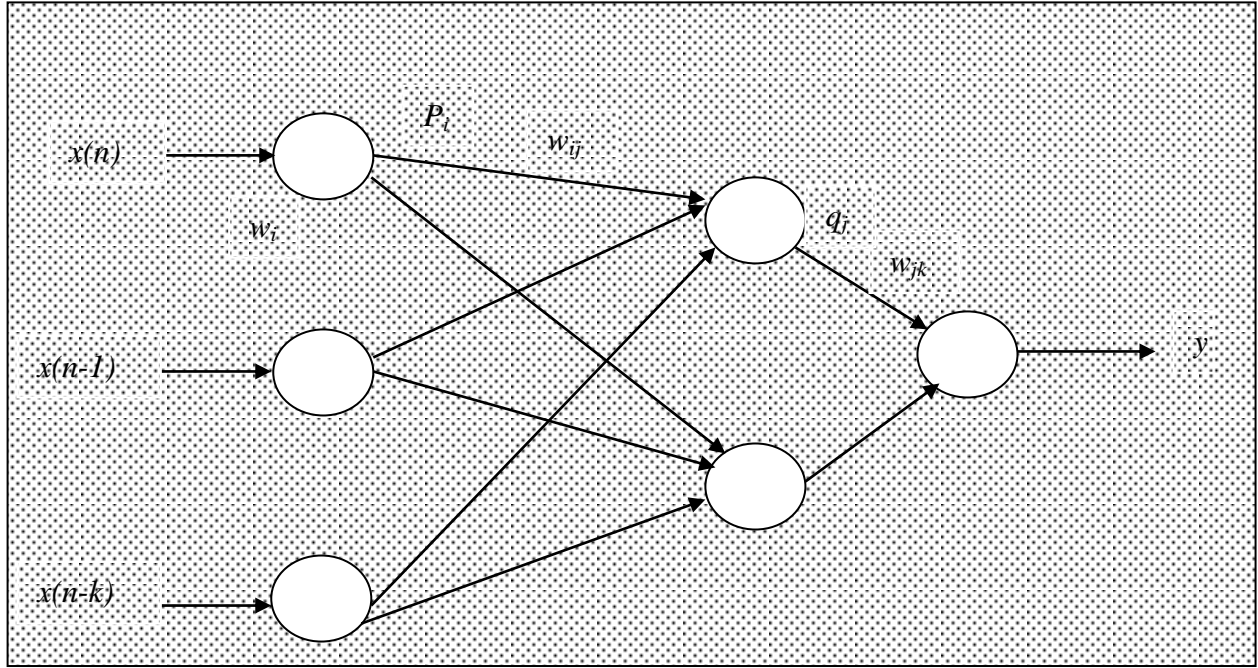


Figure 5: Two layer Feed-forward ANN architecture

From the ANN architecture shown in Figure 5, the ANN output y is computed using;

$$y = \sum q_j w_{jk} \quad (7)$$

where q_j = Input to the output node
 w_{ij} = weight of the output layer i.e is the weight of the connection between the i th and the j th unit.

The activation function used in this work is sigmoid function that scales the output in between 0 and 1. A typical sigmoid function is given by:

$$H = \frac{1}{1 + e^{-x_j}} \quad (8)$$

The output y is compared with the required output ' d ' and the total Error ' E ' is computed. The network computes the error E using the expression which is defined by:

$$E = \frac{1}{2} \sum_i (y - d)^2 \quad (9)$$

Where ' y ' is the ANN output and the ' d ' is the desired output.

The error is propagated backwards for weight update. This error derivative (EA) is the difference between the actual and the desired output.

$$EA_k = \frac{\partial E}{\partial y_k} = y - d \quad (10)$$

$$EA_k = \frac{\partial E}{\partial y} = \sum \frac{\partial E}{\partial p} \times \sum \frac{\partial E}{\partial q} = \sum EI_j w_{ij} \quad (11)$$

Where W is the weight value of the output layer

This procedure was repeated to get the EA 's for as many previous layers until the ANN output is very close to the desired output.

2.5 System Implementation

The implementation of artificial neural network based algorithm was carried out using MATLAB tool box. MATLAB is used in this study as a toolbox for comprehensive collections of MATLAB functions (M-files) which extend the MATLAB environment to solve particular classes of problems.

Since the proposed ANN algorithm is to perform cancellation of noise in speech signal, the implementation uses a classroom scenario as a case study with a background noise originating from a working standing fan. Voice is propagated as a speech signal and recorded using data acquisition system. The sentence *"this is the sound of the voice and the fan"* was acquired as MATLAB function. The acquired data is used as the primary signal in this implementation. A correlated noise signal is also acquired directly from the fan producing the background noise. This is also saved as MATLAB function and used as the reference signal. The neural network training tool is incorporated to perform the weight adaptation, therefore replacing the LMS adaptive algorithm.

The ANN based algorithm implementation is initialized by training the network. The MATLAB codes are as follows:-

```
[u,us] = mapminmax(primary1);
[y,ys] = mapminmax(desired);
y = con2seq(y);
u = con2seq(u);
p = u(3:end);
t = y(3:end);

d1 = [1:2];
d2 = [1:2];
narx_net = newnarxsp(p,t,d1,d2,10);
narx_net.trainFcn = 'trainbr';
narx_net.trainParam.show = 20;
narx_net.trainParam.epochs = 300;

Pi = [u(1:2); y(1:2)];
narx_net = train(narx_net,[p;t],t,Pi);
```

After the training, the neural network is then incorporated into ANC in order to compute the ANN output and error signal:

```
yp = sim(narx_net,[p;t],Pi);
e = cell2mat(yp) - cell2mat(t);
```

Finally, the acquired MATLAB function (both the primary signal and reference signal) given in section (3.4) is also fed into the ANN based system to perform noise cancelling adaptively.

3. Results and Discussions

3.1 Simulation Results

The simulation result of the developed ANN algorithm for sinusoidal wave signal is given in the Figure 6 and speech signal in Figure 7. The performance of the developed ANN algorithm was compared to the conventional fixed step size with different selected step size and filter order.

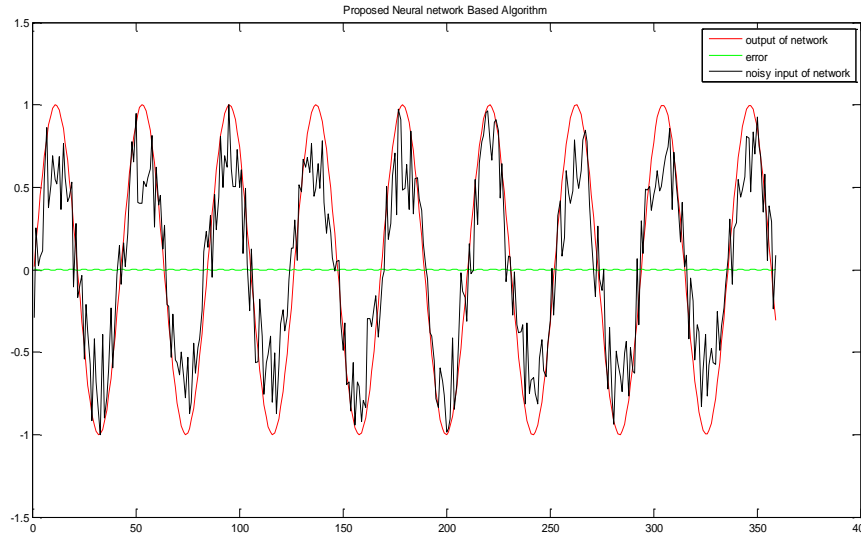


Figure 6: Regenerated sine wave signal using the developed ANN based algorithm.

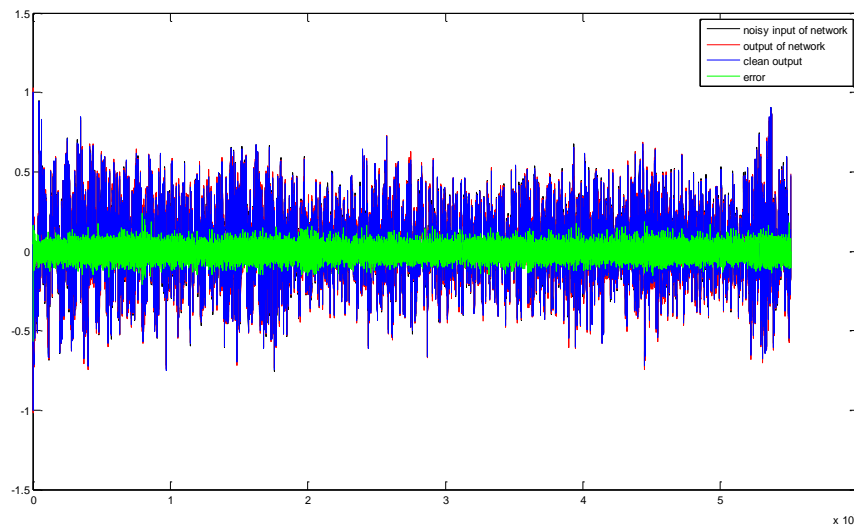


Figure 7: Simulation result of the developed neural network based algorithm for Corrupted speech signal

Figure 7 presents the adaptation of the convergence of the corrupted speech sound using the developed neural network based algorithm. The plots reveal the comparison of the corrupted noisy input signal to the network, the output of the network, the clean speech signal generated and the error.

3.2 Mean Square Error Analysis of the Developed Artificial Neural Network

The mean square error (MSE) is the measure of the squares of difference between the targeted (desired) output and system output. The performance of the developed ANN based algorithm is evaluated in terms of the MSE and compared with fixed step size LMS algorithms. Table 1 shows the simulation result comparison in terms of MSE.

Table 1: Performance evaluation of the neural network algorithm	
Algorithms	Mean Square Error (MSE)
Developed Artificial Neural Network	0.0021
Conventional LMS	0.3169

4. Conclusion

The ANN based adaptive filtering algorithm has been presented in this paper as an alternative and effective technique for noise cancellation. The proposed algorithm was successfully trained using backward propagation of error for weight update. Based on the experimental analysis and simulation results, the ANN based algorithm proves to have a good tracking capacity for non-stationary signals and thus very effective for weight adaptation. Hence, applying the developed ANN based algorithm on speech signal gives a better MSE value.

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